REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
15-11-2004

2. REPORT TYPE
Final

3. DATES COVERED (From – To)

4. TITLE AND SUBTITLE
Evolving Optimal Submunition Design for Attacking Relocatable Targets

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

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5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

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8. PERFORMING ORGANIZATOIN REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT

Distribution Statement A : Distribution Unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT

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15. SUBJECT TERMS

Simulation, Advanced Computing, Unmanned Systems, Multiobjective Optimization, Modeling, Simulation, and Gaming

16. SECURITY CLASSIFCATION: Unclassified			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
b. REPORT	b. ABSTRACT	c. THIS PAGE	UL	12	19b. TELEPHONE NUMBER (include area code)
Unclassified	Unclassified	Unclassified			

Standard Form 298 (Rev. 8-98) 298-102

Evolving Optimal Submunition Design for Attacking Relocatable Targets

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72nd MORS Symposium
Working Group 11
15 November 2004

ABSTRACT

Relocatable targets are mobile targets that will stay in a discrete location for an unknown, random length of time before moving to another location. Such targets include mobile missile launchers, air defense units, fuel trucks and other high value targets (e.g., maneuver forces). Using a combination of multiagent simulation and a multiobjective evolutionary algorithm, we evolve optimal submunition design characteristics for attacking a relocatable target. We examined three types of target concealment, and discovered that high probability of detection, short delay times, and multiple submunitions are required for successful engagement.

INTRODUCTION

A time critical target (TCT) is a fleeting, high priority target that requires an immediate response. Surface TCTs typically move rapidly and hide throughout the battlefield, limiting their exposure time (TRADOC, 1997). Relocatable targets are a subset of TCTs. This paper examines attacking relocatable targets using autonomous submunitions deployed via a missile. For various target behaviors, we optimize submunition design parameters using a multiobjective evolutionary algorithm to maximize the number of targets killed and minimize the cost. In particular, we examine target concealment and different hiding times.

BACKGROUND AND RELATED WORK

A relocatable target is a TCT that stays at a location for an unknown, random length of time before moving to another location. Such targets include mobile missile launchers and air defense units. Relocatable targets employ techniques of concealment, deception, and decoys to confuse attackers and decrease their chance of detection. Attacking relocatable targets is a priority for the United States military (Story, 1994; Quarrie, 1997); in particular, attacking mobile missile launchers. Mobile theater ballistic missile launchers use a combination of frequent movement, deception and hiding to avoid detection and attack by air assets. The proliferation of long-range mobile missiles (cruise and ballistic), which can operate deep in enemy territory, could inflict

enough damage to cause capitulation or change the political environment. For example, during the Persian Gulf War in 1991, the Iraqi Scud missiles did not pose a significant tactical threat to coalition forces. However, a major concern was that Iraq would launch Scud missiles at Israel, which might have prompted Israeli intervention causing the coalition to split (Story, 1994; Cohen 1993). These concerns were heightened by the potential use of chemical or biological warheads.

Several authors have examined attacking relocatable targets. Vick (2001) examines concepts and technologies to help the United States Air Force detect, recognize, and defeat relocatable targets. Using cooperative behavior and communications, (Frelinger et al., 1998) examines the feasibility and development of proliferated weapon concepts.

Other work has developed closed form analytical solutions for wide area search munitions (Jacques, 2002; Jacques, 1998). Using simplifying assumptions, they derive analytical formulas for probability of kill for multiple munitions searching for a target. Tabatabai develops a probabilistic approach to estimating a target location (Tabatabai, 1995). Examining the effects of autonomous weapons and dominant battlespace knowledge, (Johnson & Libicki, 1995) studies a fictional scenario to see the effects of intelligent use of autonomous weapons.

Another area of theoretical work is search theory (Koopman, 1980; Washburn, 2002). Ablavsky (2000) develops search paths for a moving target. Yang studies cooperative search among a group of UAVs (Yang et al, 2002), and (Flint et al, 2002) studies cooperative control among UAVs searching for a target.

MODEL DESCRIPTION

The model consists of two parts: modeling the flight of the submunitions, and evolving the Pareto optimal set. A multiagent simulation returns the average number of targets killed, and a multiobjective evolutionary algorithm evolves optimal submunition design characteristics. The output is a Pareto optimal set of potential combinations of submunition design characteristics. A decision maker can then choose the best solution to fit their situation.

Evolutionary computation is a family of optimization techniques based on Darwinian models of evolution (Luke, 2000; Goldberg, 1989). Each technique refines a population of candidate solutions ("individuals") to a given problem. An evolutionary algorithm (EA) begins with an initial set of randomly generated solutions to a problem. Each individual of the initial set is evaluated and assigned a fitness (a quality assessment). The EA uses a fitness based process to select, breed, and mutate the population. One cycle of selection, breeding, and mutation is called a generation. The EA continues to generate generations until time is exhausted, or a sufficiently fit individual is produced.

Multiobjective evolutionary algorithms (MOEA) evolve an optimal solution in the Pareto sense. Functioning in a manner similar to EAs, MOEAs search for solutions which simultaneously satisfy multiple objectives (i.e., solutions which approximate the Pareto front). While many MOEAs exist, we choose the Strength Pareto Evolutionary Algorithm Version 2 (SPEA2) (Zitzler et al, 2001). SPEA2 generates a good approximation to the true Pareto front, and also produces a population that is distributed along the entire front.

Multiagent Simulation

Each submunition is powered and maneuverable, but with limited range; thus, after a short period of time, the weapon will fall to the ground. The submunitions are capable of autonomous search, coordination and cooperation.

Three classes of parameters characterize an individual submunition: sensor, explosive, and communications (Table 1). Using the sensor parameters and a simple version of the radar equation, we computed the maximum range of the sensor (R_d). Similarly, using the Friis free path loss equation, we computed the maximum range of communications (R_c). If two submunitions are within range, communications occurs with probability one.

The simulation starts with the submunitions falling together on a ballistic trajectory with a terminal point of the last known target location. At a predetermined height, the submunitions split and begin searching for targets. Splitting consists of assigning each submunition a random direction, and reducing the horizontal and vertical component of its velocity.

After deployment, the submunitions follow a search path until they are within detection range, R_d, of a target. If a target never comes within range, then the submunition falls to the ground. Instantaneous detection occurs with probability P_d, and each submunition declares a detection using an at least K-out-of-N detection rule. Once a unique target (see below) is detected, then the submunition tracks the target until impact. A submunition kills a target with probability P_{kill} if it is within range, R_{kill}.

Communications consists of sharing locations of the targets each submunition can detect, and the submunitions' current position in space. Sharing detected targets prevents multiple submunitions from tracking the same target, which could reduce system performance. The submunitions use the locations to distribute themselves such that their sensors will not overlap.

The number of targets was fixed at ten. The targets follow a hide-move-hide cycle until they are destroyed or the simulation terminates. The hiding and moving times followed discrete distributions. Target concealment was modeling by changing P_d when the target is stationary. Target movement was controlled by setting a destination point. The destination point was either chosen uniformly, or in a manner to simulate movement along a grid of roads.

Table 1. The sensor, explosive, and communications parameters of each submunition.

	Parameter Name	Range
Sensor Characteristics	Probability of Detection	0 –1
	Time Between False Alarms (sec)	10 – 1800
	Bandwidth (Hz)	100 – 1000000
	Average Power (W)	10 –100
	Pulse Frequency (Hz)	10 – 10000
	Field of Regard (degrees)	0 – 90
Explosive Characteristics	Range (m)	0 – 500
	Probability of Kill	0 –1
Communications Characteristics	Transmitter Power (dBm)	0 – 100
	Transmitter Frequency (MHz)	1 – 2400
	Sensitivity Threshold (dBm)	-105 – -90

Multiobjective Evolutionary Algorithm

Several problem characteristics led us to use a MOEA over traditional optimization techniques. First, the modality of the state space is unknown. EAs can discover globally

optimum solutions in a relatively short time frame. In addition, there are unknown interactions between parameters, and we cannot predict how changing a parameter will affect the number of targets killed (i.e., we do not know how to write formulas which can be used in traditional optimization techniques). Both these characteristics require an intelligent search technique to avoid convergence to local optima and to sufficiently explore the space. Finally, we can evaluate potential solutions, and the EA can use this evaluation to determine how to explore the space and discover better solutions.

We used a MOEA to evolve a subset of optimal submunition parameters (Table 1); behavior is hard coded. Other than the two probabilities, each characteristic was varied over a range of integer values. The two probabilities were discretized in steps of 0.01. In addition, the number of submunitions varied from 5 - 20.

SPEA2 requires multiple objectives; in this case, maximize the number of targets killed and minimize the cost. The previous section described how we obtain the number of targets killed. The cost is acquired via a function based on the submunition parameters. The cost of the system is then the product of the number of submunitions and *C(Submunition)*:

$$\begin{aligned} C(Submunition) = 10 * [&C_1(\text{Comms Range}) + C_2(\text{Sensor Range}) + C_3(\text{Field Of Regard})] \\ &+ 100 * [C_4(\text{Explosive Range}) + C_5(\text{Explosive PK})] \end{aligned}$$

where C_i is an exponential function ($C_i(x_i) = K_i e^{\alpha_i x_i}$). Initial experiments built the biggest possible bomb, so we added a penalty factor to the explosive cost to increase the importance of coordination and cooperation.

EXPERIMENTS

All multiagent experiments were done on the MASON simulation environment (Luke, 2003). MASON is a fast discrete-event multiagent simulation library core in Java, designed to be the foundation for large custom-purpose Java simulations, and contains a model library and an optional suite of visualization tools in 2D and 3D.

All evolutionary computation experiments were done using the ECJ (Luke, 2000) research environment. ECJ is an open source EC and GP system written in Java. The system is capable of supporting a very wide range of evolutionary computation methods. ECJ is built to guarantee replicable results across platforms, and to permit distributed evolutionary computation procedures across clusters of machines. The library is designed to be highly flexible and very fast.

SPEA2 used 1000 generations with a population of 30. We used uniform crossover with a probability of 0.25 per gene, and a probability of mutation of 0.01. Selection was through a binary tournament with replacement. For each fitness evaluation we used 20 independent replications of the multiagent simulation, with an at least 3-out-of-5 detection rule. The number of targets killed was the median of these 20 replications.

The experiments were conducted on a nontorodial 50 km x 50 km x 10 km space with no obstacles, no false alarms, and no false targets. The target speed was 50 km/h and the munitions had a ground speed of 200 km/h. For each experiment, target behavior changed with the primary change being the ability to employ concealment. To simulate a target moving, hiding, and moving again hiding times were uniformly distributed between 0 and 5 minutes. In addition, to

simulate a target moving and staying hidden hiding times were uniformly distributed between 0 and 30 minutes.

Results

For each experiment, we computed the Pareto front for 50 independent runs. From these 50 Pareto fronts, we determined the envelope of the points to produce a single Pareto front. We investigated three variants of target concealment: none, uniform, and banded.

No Target Concealment

Since the targets do not employ concealment, hiding time does not make sense. So, we varied the time each target spends stopped. Figure 1 shows the 50 independent fronts and the corresponding envelope for the short and long stopping times respectively.

Uniform Target Concealment

The second set of experiments model target concealment by reducing P_d by a factor of 10 when the target is stationary (i.e., we assume the target hides when it is not moving). In this case, the hiding factor was independent of target location. Figure 2 shows the 50 independent fronts and the corresponding envelope for the short and long stopping times respectively.

Banded Target Concealment

The final set of experiments modeled multiple hiding places by dividing the space into concentric circular bands centered at the initial target location. As the target moves away from the initial location, P_d becomes

$$P_d = \frac{P_d}{10^i}$$

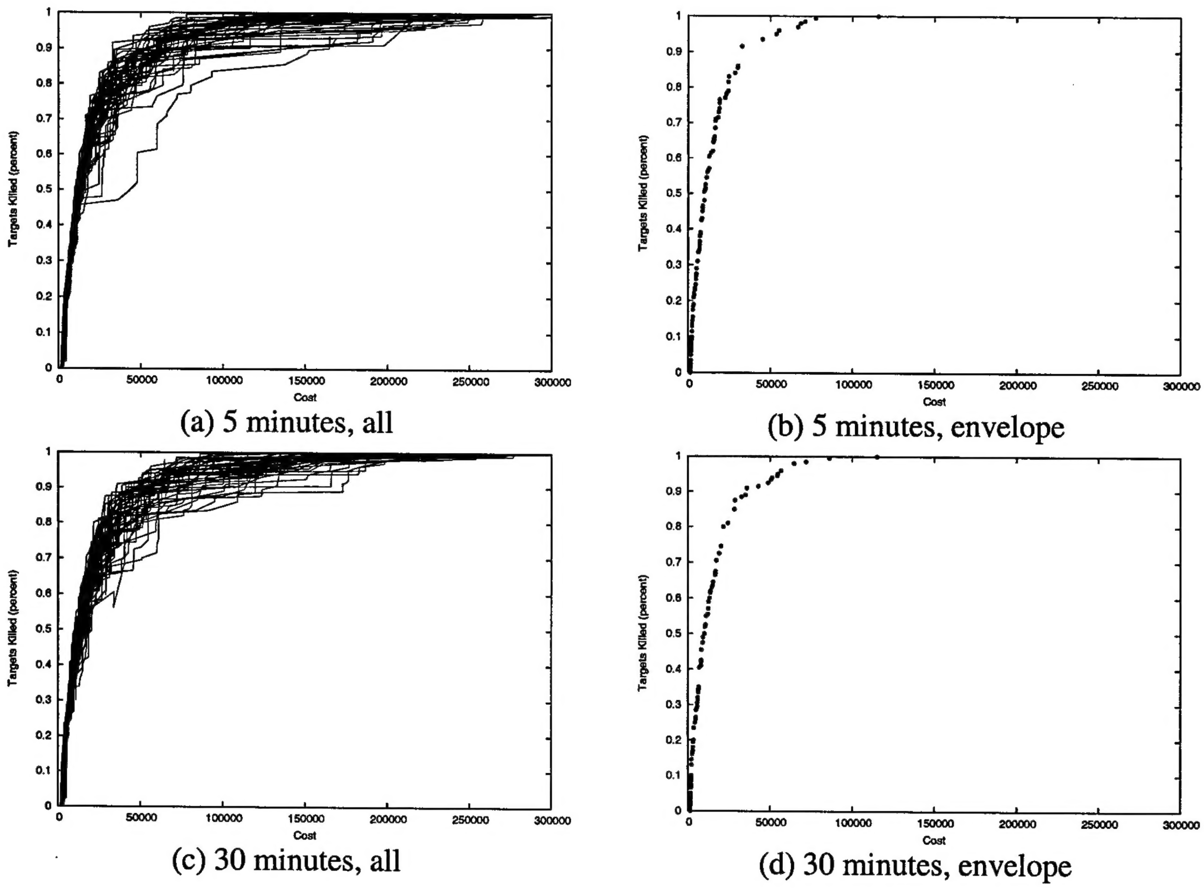
where i is the band the target is currently in. Figure 3 shows the results for 1 km wide bands, and figure 4 shows the results for 10 km wide bands.

Discussion

In trying to understand the results, we choose representative points from each global Pareto front, and examined the system characteristics (see Table 2 for uniform concealment and no concealment, and Table 3 for banded target concealment).

Across all the experiments, every combination of hiding time and target concealment requires nearly twice as many munitions as targets. While this does assist in the high percentage of targets killed, it has significant drawbacks in implementation. Recall that we are not modeling the delivery vehicle, thus, we do not have the cost and/or the performance of the delivery vehicle included. To see the impact of the delivery vehicle, assume the delivery vehicle is a Minuteman III with a throw weight of approximately 2500 pounds (Janes, 2004) (The Minuteman is one of the largest missiles currently in use). Assuming each submunition weights 100 pounds, a single Minuteman could conceivably launch every submunition combination studied here (packing issues might dictate otherwise). However, each Minuteman booster costs $7 million (U.S. Air Force, 2002), making this an expensive way to attack TCTs.

As the banded results indicate, the faster a weapon arrives on target the better. As target concealment increases, the system cost drastically increases to achieve the same level of



(a) 5 minutes, all

(b) 5 minutes, envelope

(c) 30 minutes, all

(d) 30 minutes, envelope

Figure 1. For no concealment, the 50 independent Pareto fronts and the corresponding envelope.

performance. Thus, implementation could become quite expensive if a system is to attack a general target.

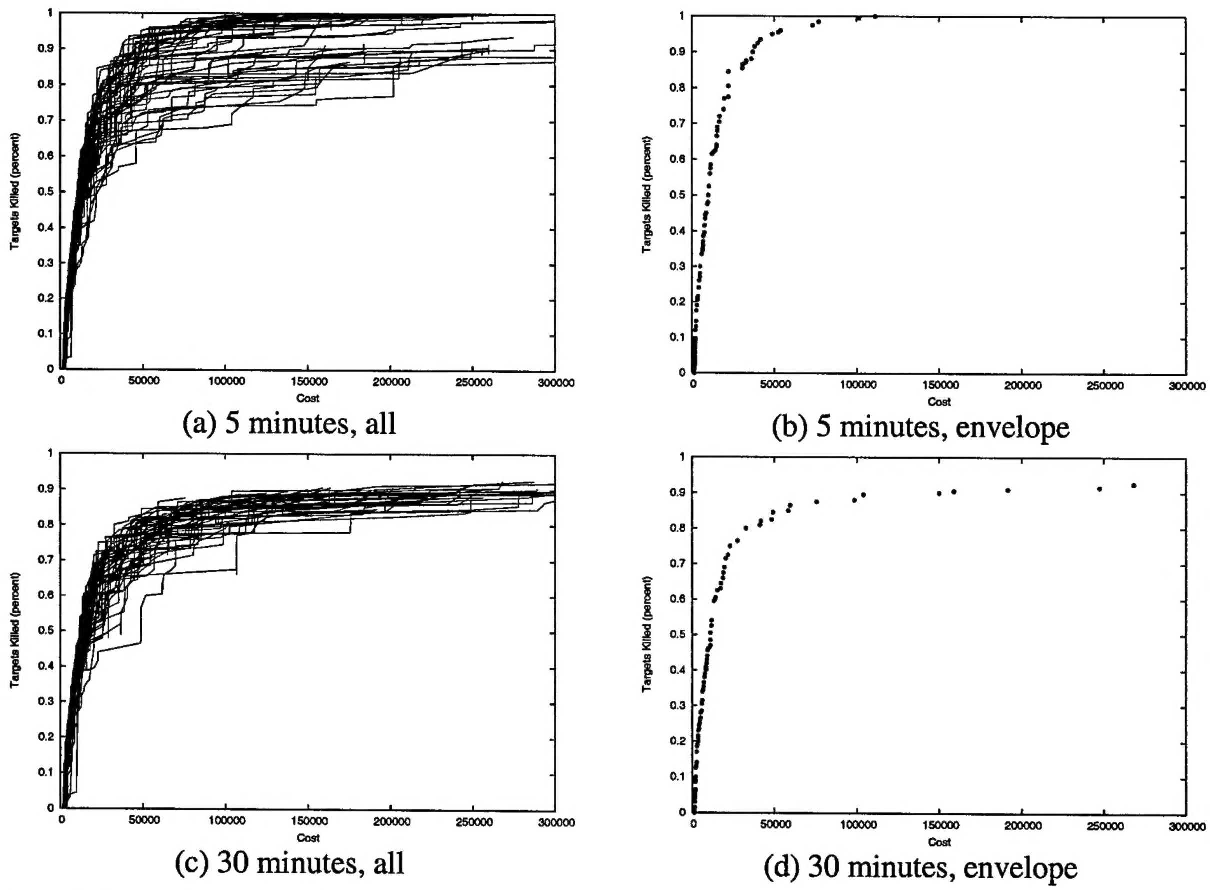
Another factor to note is the high probability of detection. While one expects a high P_d – since the submunitions cannot do anything if they do not have a detection – the probability of detection is high, especially since we made no assumptions about the target nor the type of sensor.

As the hiding times increase, the algorithm compensates by increasing the explosive characteristics despite the high penalty factor. Despite increased communications performance, this implies that when targets are hiding cooperation and coordination are not particularly effective means to increase the number of targets killed.

CONCLUSION AND FUTURE WORK

Using multiagent simulation and MOEAs we presented a methodology for finding optimal submunition design characteristics for several variants of target concealment.

The primary avenue for future work is developing realistic target motion algorithms. Other future work includes adding environmental effects (i.e., weather, terrain) and adding false alarms and decoys.



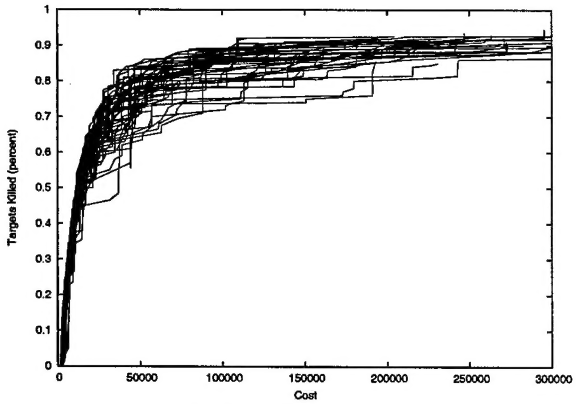
(a) 5 minutes, all

(b) 5 minutes, envelope

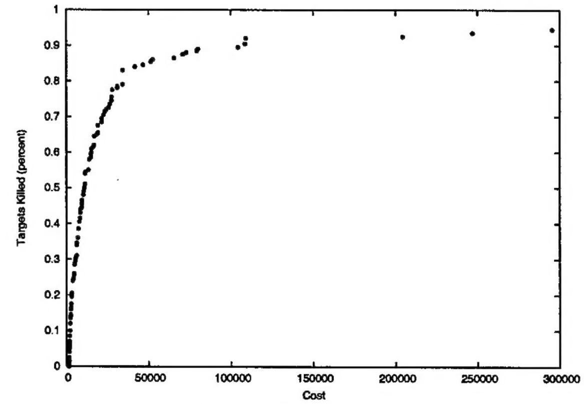
(c) 30 minutes, all

(d) 30 minutes, envelope

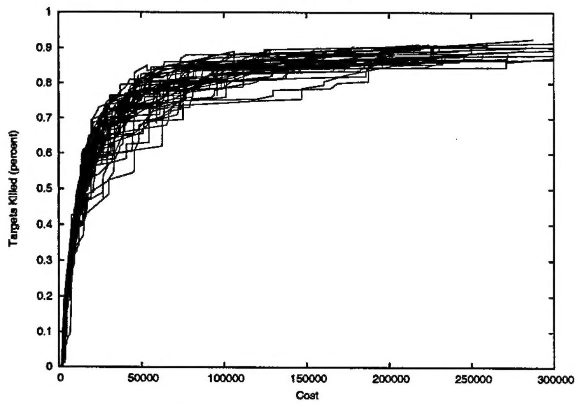
Figure 2. For uniform concealment, the 50 independent Pareto fronts and the corresponding envelope.



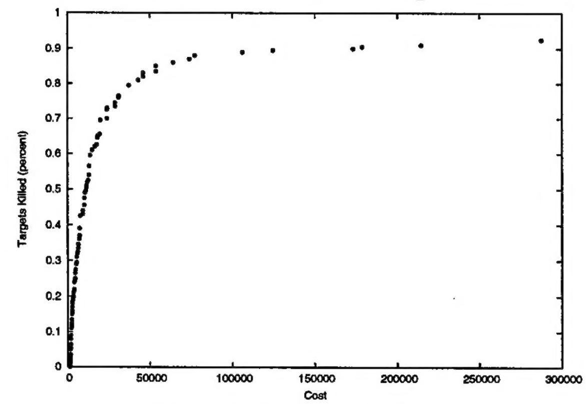
(a) 5 minutes, all



(b) 5 minutes, envelope

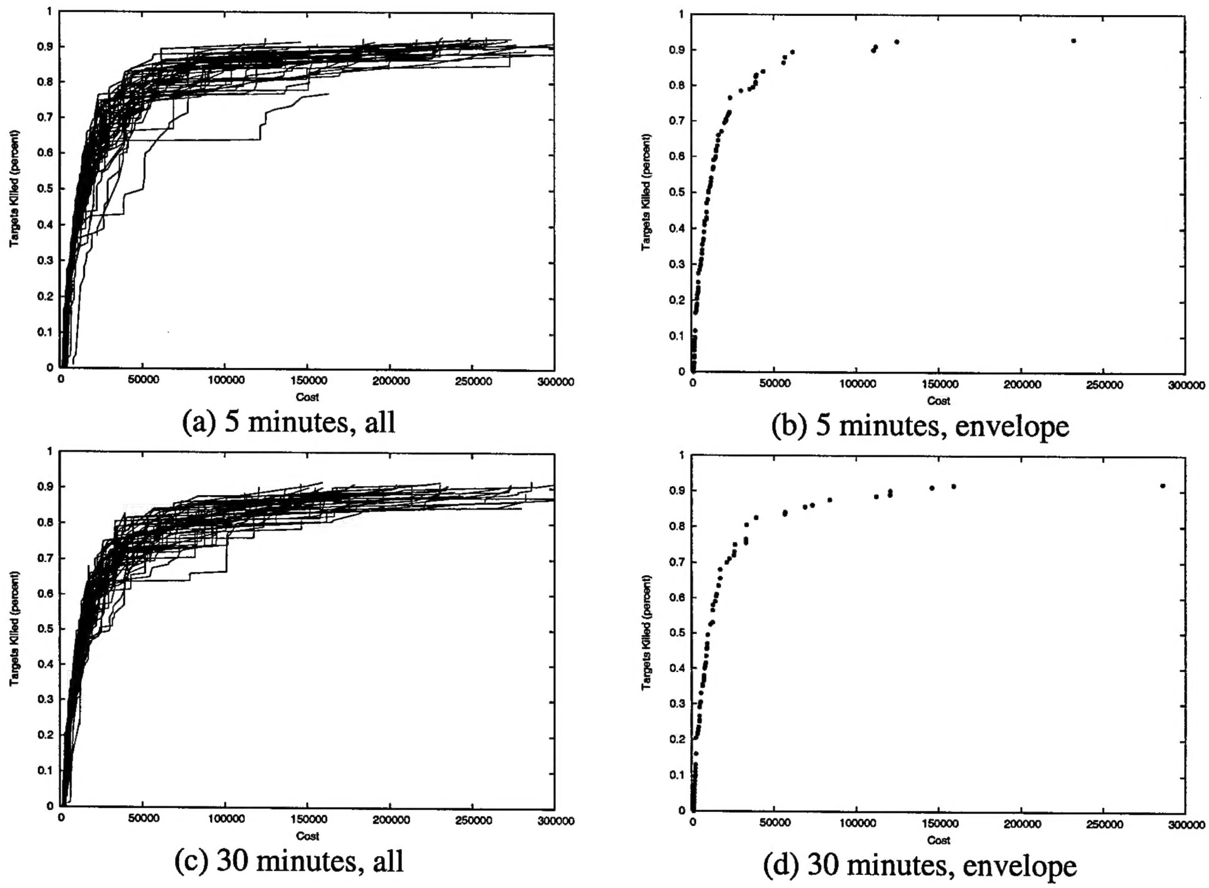


(c) 30 minutes, all



(d) 30 minutes, envelope

Figure 3. For the 1 km band, the 50 independent Pareto fronts and the corresponding envelope.



(a) 5 minutes, all

(b) 5 minutes, envelope

(c) 30 minutes, all

(d) 30 minutes, envelope

Figure 4. For the 10 km band, the 50 independent Pareto fronts and the corresponding envelope.

Table 2. A representative of the sensor, explosive, and communications parameters of each submunition for uniform concealment.

	No Concealment		Uniform Concealment	
Parameter Name	**5 minutes**	**30 minutes**	**5 minutes**	**30 minutes**
Number of Submunitions	19	18	15	19
Probability of Detection	0.94	0.95	0.99	0.97
Time Between False Alarms (sec)	1668	865	1744	1726
Bandwidth (Hz)	317224	548916	930428	819593
Average Power (W)	69	39	72	81
Pulse Frequency (Hz)	4586	1836	3570	7957
Field of Regard (degrees)	72	85	67	59
Range (m)	74	124	90	79
Probability of Kill	0.53	0.63	0.66	0.79
Transmitter Power (dBm)	4	1	1	1
Transmitter Frequency (MHz)	2395	2348	1658	2075
Sensitivity Threshold (dBm)	-90	-91	-90	-90
Percentage Targets Killed	0.915	0.935	0.935	0.895
Cost	32777	49296	45384	103944

Table 3. A representative of the sensor, explosive, and communications parameters of each submunition for banded target concealment.

	1 km Band		10 km Band	
Parameter Name	**5 minutes**	**30 minutes**	**5 minutes**	**30 minutes**
Number of Submunitions	18	18	19	15
Probability of Detection	0.99	0.97	0.99	0.97
Time Between False Alarms (sec)	1200	1676	1473	1174
Bandwidth (Hz)	856396	45158	728170	976424
Average Power (W)	84	68	81	81
Pulse Frequency (Hz)	9989	7074	8528	4863
Field of Regard (degrees)	75	83	85	90
Range (m)	90	61	59	76
Probability of Kill	0.81	0.84	0.68	0.87
Transmitter Power (dBm)	1	1	1	2
Transmitter Frequency (MHz)	1831	2340	1947	2372
Sensitivity Threshold (dBm)	-91	-93	-90	-91
Percentage Targets Killed	0.92	0.895	0.895	0.90
Cost	109005	124610	61540	120597

ACRONYMS AND ABBREVIATIONS

TCT	Time Critical Target
EA	Evolutionary Algorithm
MOEA	Multiobjective Evolutionary Algorithm
SPEA2	Strength Pareto Evolutionary Algorithm, Version 2

DESCRIPTORS

Simulation
Advanced Computing
Unmanned Systems
Multiobjective Optimization
Modeling, Simulation, and Gaming

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